Spatial soil moisture mapping through multi-temporal analysis of ERS-SAR PRI data

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Abstract

The scattering of microwaves from soil depends on several surface characteristics, such as the roughness, vegetation and the moisture content of the top layer. Knowledge of the temporal and spatial distribution of this last parameter is of major importance to hydrologic, meteorologic and climatologic modelling. However accurate measurements of the spatial distribution of soil moisture with classical methods have always been a difficult task. Owing to its dependency on soil moisture and its spatial character, radar remote sensing holds much promise. Several empirical and physically based scattering models have been proposed to retrieve soil moisture values from SAR data, but problems occur with the identification of the roughness and vegetation parameters. This can be partly overcome through the use of multi-frequency and/or multi-polarization radar, but this option is often not available on spaceborne platforms. However, single frequency and single polarization data allows one to map saturation-prone areas using a multi-temporal analysis. The use of multi-temporal data makes it possible to retrieve spatial moisture patterns within the studied catchment by applying statistical methods to the time series of images.

Two methods for the analysis of a winter time series of ERS-1 and ERS-2 images, for which constant roughness and vegetation conditions can be assumed, are suggested. The first method is based on the temporal coefficient of variation. Since the variability of soil moisture is expected to be smaller near a stream then further upslope from the stream, a smaller temporal coefficient of variation of the returned signal is observed near streams. The second method makes use of principal component analysis of the winter time series of images. Both methods lead to a representation of the spatial distribution of the soil moisture at the catchment scale. However, principal component transformation performs better since it can separate the soil moisture component in the backscattered signal from other influencing factors such as topography and land use.

Keywords: Soil moisture, Coefficient of variation, Principal component analysis

Introduction

Radar remote sensing has been shown to be a useful tool for the determination of the spatial soil moisture distribution within a catchment. Nevertheless, to get exact values for this parameter, a lot of information has to be known, such as the roughness characteristics of the soil and the vegetation characteristics. It has been shown that with multi-frequency data the soil moisture content and effective roughness parameters could be derived for bare soil surfaces (Su et al., 1996) . This procedure cannot be used for single-frequency single-polarization satellite data, such as from ERS satellites.

The first part of this paper presents the time series of images for the analysis. In the second section the use of the temporal coefficient of variation for deriving soil moisture patterns is discussed. Section three discusses principal component analysis for this purpose. Finally, differences between both methods are discussed.

Experimental site and discription of data

The selected study area for the analysis is the Zwalm catchment, which is located about 20 km south of Gent, Belgium. The land use in the catchment is mostly agricultural but the southern is forested. The degree of urbanization is about 10%.

For temporal analysis of soil moisture using radar images, it is desirable to examine a period over which marginal changes in roughness and vegetation are expected. In our application the winter period of October 1995 to March 1996 was chosen. During this period it can be assumed that changes in backscattering are mainly due to changes in moisture content of the toplayer. Figure 1 gives an overview of the daily rainfall during the selected peroid and also shows the data takes of ERS-1 and ERS-2 which are used in the analysis.

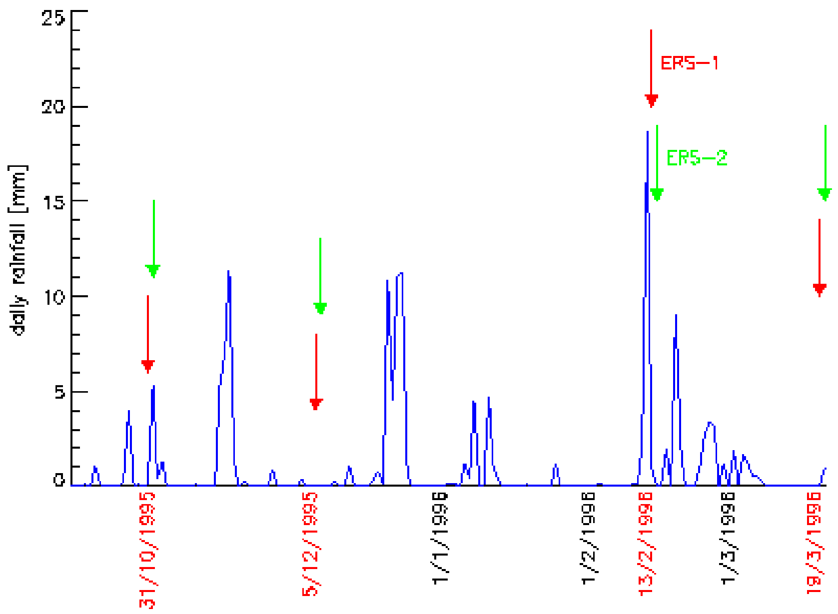

Figure 1: Daily rainfall over the 1995-1996 winter period. Also indicated are the ERS-1 and ERS-2 data takes.

4 descending ERS-1 and 4 descending ERS-2 images were selected, on the following dates:

31/10/1995: ERS-1, D-PAF
01/11/1995: ERS-2, D-PAF
05/12/1995: ERS-1, I-PAF
06/12/1995: ERS-2, I-PAF
13/02/1996: ERS-1, I-PAF
14/02/1996: ERS-2, D-PAF
19/03/1996: ERS-1, I-PAF
20/03/1996: ERS-2, I-PAF

All images share the same frame and track (resp. 2583 and 423), for which the local incidence angle for each pixel can be assumed to be constant in time. This is an important consideration since effects of changes in incidence angles can be noticed on the backscattering (Altese et al., 1996) .

After georeferencing, the images were resampled to 30 by 30 meter pixels. Since the images were obtained from two different Processing and Archiving Facilities (PAFs), all images were calibrated to the same reference (ERS-1 I-PAF). The final preliminary image processing step to be performed is speckle reduction. In our study we applied the Gamma MAP filter designed by Lopez et al. (1990), which gives very high speckle reduction.

Temporal coefficient of variation

For the analysis of a series of ERS-1 images, (Gineste and M&eacuterot, 1996) suggested 4 different parameters, called radar indices. One of these indices is the temporal coefficient of variation (CV), which can be calculated as the temporal standard deviation of a pixel divided by its temporal mean value.

Since the variation of soil moisture near rivers is expected to be small compared to the variation in upslope areas, this analysis should produce less signal variation and thus a smaller CV near the rivers, and increasing signal variation further away.

After calculating the coefficient of variation on the sequence of 8 images, lower CV values are indeed observed near the rivers, as shown in Figure 2 . However, the influence of topography and land use can also clearly be seen: forested areas in the south of the catchment and scattered urbanized areas also produce low CV values.

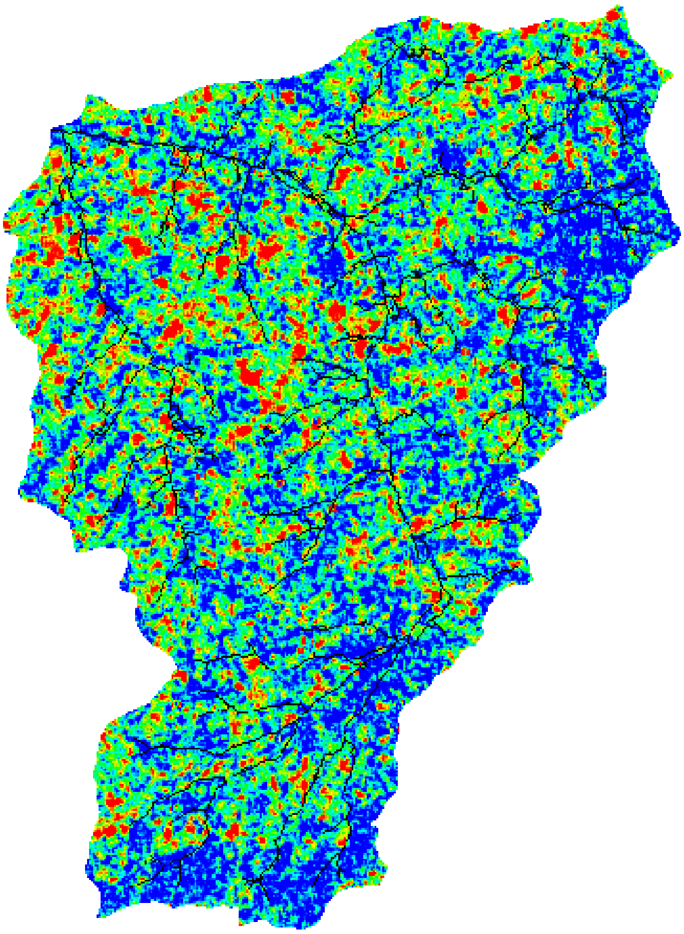

Figure 2: Coefficient of variation over the 8 ERS images. The stream network (black) is draped on top of the image.

Principal component analysis

The principal component transformation is a linear transformation which uses image data statistics to define a rotation of original images in such a way that the new axes are orthogonal to each other and point in the direction of decreasing order of variances. In optical remote sensing this transformation has been widely used for image enhancement, digital change detection, data compression and classification (Richards, 1990, Gonzales and Wintz, 1987, Singh, 1989). Principal component analysis has not been widely used in radar remote sensing. One example is provided by Lee and Hoppel (1992)), who use a modified principal component transformation on multifrequency polarimetric SAR imagery for reducing speckle and information compression. Subjecting the 8 ERS images to a principal component analysis leads to the separation of the signal into several components which can be assigned to different factors influencing the backscattering. After ordering the eigenvalues in a descending sequence, the corresponding eigenvectors point in the direction of decreasing variances (see Table 1).

Matrix of Eigenvectors	Variance (%)
(-0.33,-0.32,-0.30,-0.27,-0.45,-0.39,-0.38,-0.35)	87.6
(-0.32,-0.27,-0.35,-0.41,0.70,0.20,0.04,-0.01)	3.77
(0.32,0.32,-0.06,-0.21,0.34,-0.79,0.06,0.00)	3.02
(-0.33,-0.28,0.00,-0.05,-0.22,-0.29,0.60,0.56)	2.53
(-0.39,-0.27,0.58,-0.44,0.35,-0.28,-0.16,-0.17)	1.51
(-0.58,0.68,0.27,-0.35,-0.09,0.08,0.04,-0.06)	0.70
(0.31,-0.33,0.61,-0.63,-0.08,0.08,0.05,-0.07)	0.54
(0.01,-0.02,-0.07,0.09,-0.03,0.02,0.68,-0.72)	0.31

Table 1: The Coefficients of the Eigenvectors for each Principal Component (PC) and the Percentage of the Total Data Variance Accounted for in each PC.

For our application, 87,6% of the variance (information) within the image is explained by the first component. This component will correspond to the mean behaviour of the catchment towards backscattering during this period, and will be influenced mainly topography (e.g. larger backscattering on the slopes facing the satellite). The second principal component in our analysis accounts for 3.77% of the variance within the image. This component appears to be mainly influenced of urbanized areas and land use.

The third principal component, appears to map those pixels that have a similar behaviour in soil moisture dynamics, as can be seen in Figure 3 . The dentritic network is clearly visible and is extended by those pixels that have constantly high soil moisture content. It can be reasoned that these areas are related to the variable source areas generating saturation excess overland flow during rainstorms. The fourth and subsequent components are probably characterized mostly by noise, and account for 5.59% of the image.

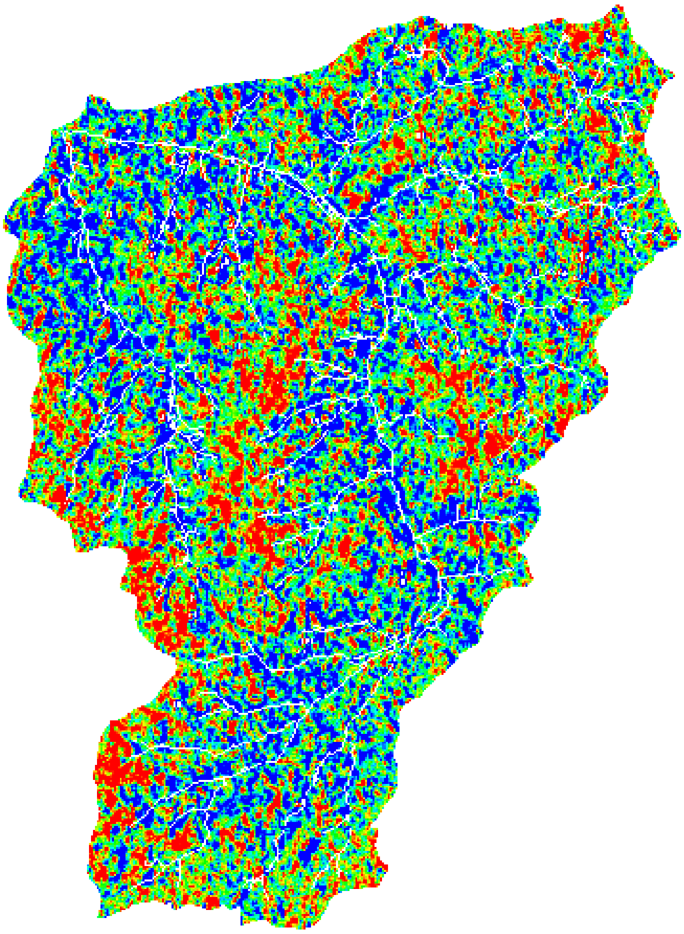

Figure 3: Third principal component retrieved from 8 ERS images. The stream network (white) is draped on top of the image.

Conclusions

For the determination of soil moisture patterns using temporal SAR data, we have selected a series of 8 ERS images taken over a winter period, all sharing the same frame and track, to minimize the effects of local incidence angle, vegetation, and soil surface characteristics. In this paper two methods were presented for the determination of the soil moisture distribution in a catchment. A first method makes use of the temporal coefficient of variation, but suffers from topographical and land use effects. Low values of CV are observed near the stream and higher values occur in upslope areas. The main drawback of this analysis is that it is impossible to distinguish between the influences of topography, land use, and soil moisture on backscattering, which results in corrupted maps of saturation-prone areas.

The second method applied is a principal component analysis on the SAR images. This statistical technique makes it possible to separate the soil moisture effects from the governing topographical and land use influences on the backscattering and thus allows us to map the soil moisture distribution within the catchment during a winter season.

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